Build various CNN networks on MNIST dataset.

Exercise :

1. Use MNIST dataset, which is present in keras datasets.
2. Also try 3-different convolution model, with 3,5 and 7 convolution layer.
3. Try 3-different kernels like 3X3, 4X4 and 5X5 kernels.
4. Also use dropout and batch normalization and plot train-test error vs epochs for each model.
5. Write your observations in English as crisply and unambiguously as possible. Always quantify your results.

Information regarding data set :

1. **Title**: MNIST database of handwritten digits
2. **Sources**: Modified National Institute of Standards and Technology(MNIST)
3. **Relevant Information**: The MNIST database of handwritten digits, available from the page(http://yann.lecun.com/exdb/mnist/), has a training set of 60,000 examples, and a test set of 10,000 examples. It is a subset of a larger set available from NIST. The digits have been size-normalized and centered in a fixed-size image..

In [1]:
```
import warnings
from sklearn.exceptions import DataConversionWarning
warnings.filterwarnings(action='ignore', category=DataConversionWarning)

# For plotting purposes
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from keras.utils import to_categorical
from keras.models import Sequential
from keras.initializers import he_normal
from keras.layers import BatchNormalization, Conv2D, Dense, Dropout, Flatten, MaxPooling2D
from keras import backend as K

# Import MNIST Dataset
from keras.datasets import mnist
```

```
Using TensorFlow backend.
```

In [2]:
```
# Load and split MNIST dataset
(x_train,y_train),(x_test,y_test) = mnist.load_data()
```

In [3]:
```
print("x_train shape: ", x_train.shape)
print("x_test shape: ", x_test.shape)
print("Number of training examples :", x_train.shape[0], "and each image is of shape (%d, %d)"%(x_train.shape[1], x_train.shape[2]))
print("Number of testing examples :", x_test.shape[0], "and each image is of shape (%d, %d)"%(x_test.shape[1], x_test.shape[2]))
```

```
x_train shape:  (60000, 28, 28)
x_test shape:  (10000, 28, 28)
Number of training examples : 60000 and each image is of shape (28, 28)
Number of testing examples : 10000 and each image is of shape (28, 28)
```

In [4]:
```
# Input image dimensions
image_rows, image_columns = 28, 28

# Number of target class labels
target_class_label_count = 10

# Input shape
input_shape = tuple()

if K.image_data_format() == 'channels_first':
    # Theano dimension order
    x_train = x_train.reshape(x_train.shape[0], 1, image_rows, image_columns)
    x_test = x_test.reshape(x_test.shape[0], 1, image_rows, image_columns)
    input_shape = (1, image_rows, image_columns)
else:
    # TensorFlow dimension order
    x_train = x_train.reshape(x_train.shape[0], image_rows, image_columns, 1)
    x_test = x_test.reshape(x_test.shape[0], image_rows, image_columns, 1)
    input_shape = (image_rows, image_columns, 1)

print("Input shape: ",input_shape)

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

x_train /= 255
x_test /= 255

print('x_train shape:', x_train.shape)
print('x_test shape:', x_test.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

# Convert class vectors to binary class matrices
y_train = to_categorical(y_train,target_class_label_count)
y_test = to_categorical(y_test,target_class_label_count)
```

```
Input shape:  (28, 28, 1)
x_train shape: (60000, 28, 28, 1)
x_test shape: (10000, 28, 28, 1)
60000 train samples
10000 test samples
```

In [5]:
```
# Plot train and cross validation loss
def plot_train_cv_loss(trained_model, epochs, colors=['b']):
    fig, ax = plt.subplots(1,1)
    ax.set_xlabel('epoch')
    ax.set_ylabel('Categorical Crossentropy Loss')
    x_axis_values = list(range(1,epochs+1))

    validation_loss = trained_model.history['val_loss']
    train_loss = trained_model.history['loss']

    ax.plot(x_axis_values, validation_loss, 'b', label="Validation Loss")
    ax.plot(x_axis_values, train_loss, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

Model 1 : with 3-Convolution Layer and 3X3 kernel

In [6]:
```
# Batch size
batch_size = 128

# Number of time whole data is trained
epochs = 15

# 3X3 kernel
kernel_3X3 = (3,3)

# 5X5 kernel
kernel_5X5 = (5,5)

# 7X7 kernel
kernel_7X7 = (7,7)

# 2X2 max pool
max_pool_2X2 = (2,2)

# 3X3 max pool
max_pool_3X3 = (3,3)

# 4X4 max pool
max_pool_4X4 = (4,4)
```

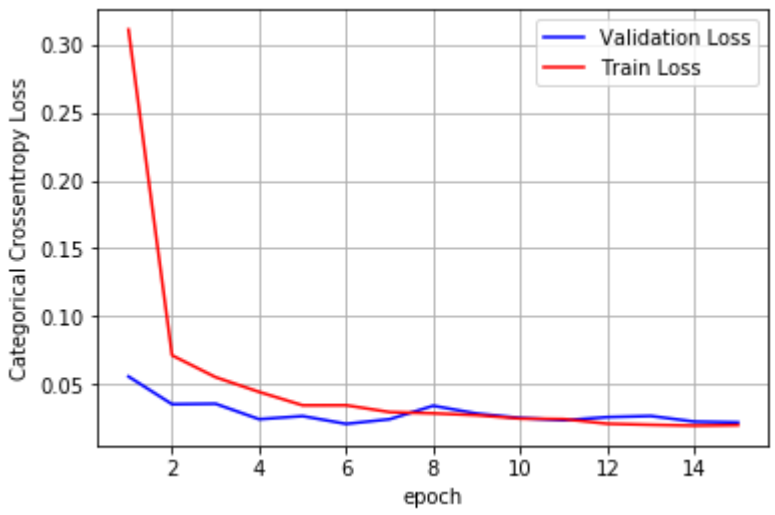
In [7]:
```
# Instantiate sequential model
model = Sequential()

# Add 1st hidden layer : Convolution Layer 1
conv_layer1 = Conv2D(32,
                     kernel_size=kernel_3X3,
                     activation="relu",
                     input_shape=input_shape)
model.add(conv_layer1)

# Add batch normalization
model.add(BatchNormalization())

# Add dropout
model.add(Dropout(0.25))


# Add 2nd hidden layer : Convolution Layer 2
conv_layer2 = Conv2D(64,
                     kernel_size=kernel_3X3,
                     activation="relu")
model.add(conv_layer2)

# Add max pooling layer
model.add(MaxPooling2D(pool_size=max_pool_2X2))

# Add dropout
model.add(Dropout(0.50))

# Add 3rd hidden layer : Convolution Layer 3
conv_layer3 = Conv2D(128,
                     kernel_size=kernel_3X3,
                     activation="relu")
model.add(conv_layer3)

# Add max pooling layer
model.add(MaxPooling2D(pool_size=max_pool_2X2))

# Add dropout
model.add(Dropout(0.25))

# Convert data to 1-D array and perform normal MLP
model.add(Flatten())

# Convert to dense layer
model.add(Dense(128, activation='relu'))

# Output layer
model.add(Dense(target_class_label_count, activation='softmax'))


# Summary of the model
print("Model Summary: \n")
model.summary()
print()
print()

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])


# Run the model
trained_model = model.fit(x_train, y_train, batch_size = batch_size, epochs = epochs, verbose=1, valid
ation_data=(x_test, y_test))
```

```
Model Summary:

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
batch_normalization_1 (Batch (None, 26, 26, 32)        128
_________________________________________________________________
dropout_1 (Dropout)          (None, 26, 26, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 24, 24, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 12, 12, 64)        0
_________________________________________________________________
dropout_2 (Dropout)          (None, 12, 12, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 10, 10, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 128)         0
_________________________________________________________________
dropout_3 (Dropout)          (None, 5, 5, 128)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 3200)              0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               409728
_________________________________________________________________
dense_2 (Dense)              (None, 10)                1290
=================================================================
Total params: 503,818
Trainable params: 503,754
Non-trainable params: 64
_________________________________________________________________


Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 136s 2ms/step - loss: 0.3111 - acc: 0.9070 - val_loss:
0.0557 - val_acc: 0.9847
Epoch 2/15
60000/60000 [==============================] - 135s 2ms/step - loss: 0.0713 - acc: 0.9779 - val_loss:
0.0354 - val_acc: 0.9879
Epoch 3/15
60000/60000 [==============================] - 132s 2ms/step - loss: 0.0552 - acc: 0.9825 - val_loss:
0.0357 - val_acc: 0.9881
Epoch 4/15
60000/60000 [==============================] - 131s 2ms/step - loss: 0.0444 - acc: 0.9860 - val_loss:
0.0243 - val_acc: 0.9917
Epoch 5/15
60000/60000 [==============================] - 133s 2ms/step - loss: 0.0346 - acc: 0.9892 - val_loss:
0.0266 - val_acc: 0.9925
Epoch 6/15
60000/60000 [==============================] - 130s 2ms/step - loss: 0.0346 - acc: 0.9886 - val_loss:
0.0209 - val_acc: 0.9932
Epoch 7/15
60000/60000 [==============================] - 129s 2ms/step - loss: 0.0296 - acc: 0.9911 - val_loss:
0.0243 - val_acc: 0.9918
Epoch 8/15
60000/60000 [==============================] - 130s 2ms/step - loss: 0.0287 - acc: 0.9908 - val_loss:
0.0342 - val_acc: 0.9895
Epoch 9/15
60000/60000 [==============================] - 128s 2ms/step - loss: 0.0273 - acc: 0.9912 - val_loss:
0.0285 - val_acc: 0.9920
Epoch 10/15
60000/60000 [==============================] - 131s 2ms/step - loss: 0.0248 - acc: 0.9917 - val_loss:
0.0252 - val_acc: 0.9923
Epoch 11/15
60000/60000 [==============================] - 134s 2ms/step - loss: 0.0244 - acc: 0.9922 - val_loss:
0.0236 - val_acc: 0.9931
Epoch 12/15
60000/60000 [==============================] - 131s 2ms/step - loss: 0.0210 - acc: 0.9933 - val_loss:
0.0259 - val_acc: 0.9923
Epoch 13/15
60000/60000 [==============================] - 136s 2ms/step - loss: 0.0202 - acc: 0.9934 - val_loss:
0.0267 - val_acc: 0.9935
Epoch 14/15
60000/60000 [==============================] - 134s 2ms/step - loss: 0.0196 - acc: 0.9938 - val_loss:
0.0225 - val_acc: 0.9941
Epoch 15/15
60000/60000 [==============================] - 138s 2ms/step - loss: 0.0200 - acc: 0.9933 - val_loss:
0.0220 - val_acc: 0.9935
```

In [8]:
```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy: {0:.2f}%'.format(score[1]*100))
```

```
Test score: 0.021964074645725123
Test accuracy: 99.35%
```

In [9]:
```
print()
print()

# Plot train and cross validation error
plot_train_cv_loss(trained_model, epochs)
```



On 13th epoch we find that validation error and train error comes together and then after follows the same path, so best value for epoch is between 13-14

Model 2 : with 5-Convolution Layer and 5X5 kernel

In [10]:
```
%%time

# Instantiate sequential model
model = Sequential()

# Add 1st hidden layer : Convolution Layer 1
conv_layer1 = Conv2D(16,
                         kernel_size=kernel_5X5,
                         activation="relu",
                         input_shape=input_shape,
                         kernel_initializer='he_normal')
model.add(conv_layer1)
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=max_pool_3X3,strides=(1,1),padding="same"))
model.add(Dropout(0.25))


# Add 2nd hidden layer : Convolution Layer 2
conv_layer2 = Conv2D(32,
                        kernel_size=kernel_5X5,
                        activation="relu",
                        kernel_initializer='he_normal')
model.add(conv_layer2)
model.add(MaxPooling2D(pool_size=max_pool_3X3,strides=(1,1),padding="same"))
model.add(Dropout(0.25))


# Add 3rd hidden layer : Convolution Layer 3
conv_layer3 = Conv2D(64,
                        kernel_size=kernel_5X5,
                        activation="relu",
                        kernel_initializer='he_normal')
model.add(conv_layer3)
model.add(MaxPooling2D(pool_size=max_pool_3X3,strides=(1,1),padding="same"))
model.add(Dropout(0.25))

# Add 4th hidden layer : Convolution Layer 4
conv_layer4 = Conv2D(128,
                        kernel_size=kernel_5X5,
                        activation="relu",
                        kernel_initializer='he_normal')
model.add(conv_layer4)
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=max_pool_3X3,strides=(1,1),padding="same"))
model.add(Dropout(0.50))


# Add 5th hidden layer : Convolution Layer 5
conv_layer5 = Conv2D(256,
                        kernel_size=kernel_5X5,
                        activation="relu",
                        kernel_initializer='he_normal')
model.add(conv_layer5)
model.add(MaxPooling2D(pool_size=max_pool_3X3,strides=(1,1),padding="same"))
model.add(Dropout(0.50))


# Convert data to 1-D array and perform normal MLP
model.add(Flatten())

# Convert to dense layer
model.add(Dense(260, activation='relu'))

# Convert to dense layer
model.add(Dense(130, activation='relu'))

# Add batch normalization
model.add(BatchNormalization())

# Add dropout
model.add(Dropout(0.50))

# Output layer
model.add(Dense(target_class_label_count, activation='softmax'))


# Summary of the model
print("Model Summary: \n")
model.summary()
print()
print()

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Run the model
trained_model = model.fit(x_train, y_train, batch_size = batch_size, epochs = epochs, verbose=1, valid
```

```
ation_data=(x_test, y_test))
```

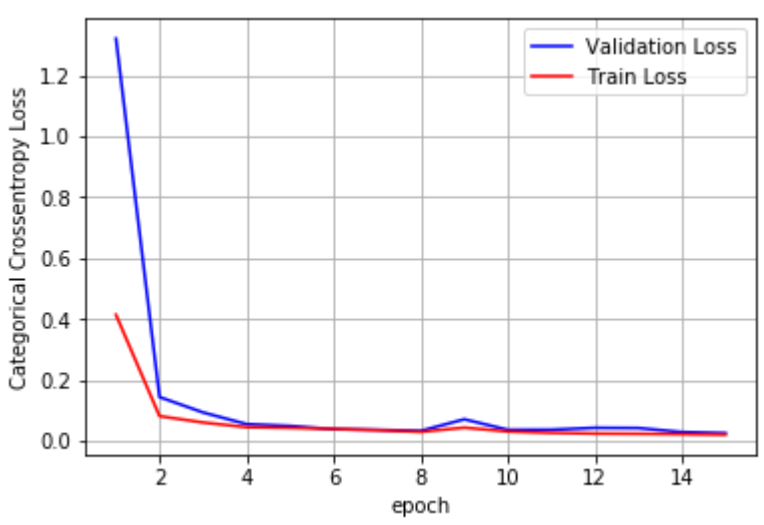
```
Model Summary:

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 24, 24, 16)        416
_________________________________________________________________
batch_normalization_2 (Batch (None, 24, 24, 16)        64
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 24, 24, 16)        0
_________________________________________________________________
dropout_4 (Dropout)          (None, 24, 24, 16)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 20, 20, 32)        12832
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 20, 20, 32)        0
_________________________________________________________________
dropout_5 (Dropout)          (None, 20, 20, 32)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 16, 16, 64)        51264
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
dropout_6 (Dropout)          (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 12, 12, 128)       204928
_________________________________________________________________
batch_normalization_3 (Batch (None, 12, 12, 128)       512
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 12, 12, 128)       0
_________________________________________________________________
dropout_7 (Dropout)          (None, 12, 12, 128)       0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 8, 8, 256)         819456
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 8, 8, 256)         0
_________________________________________________________________
dropout_8 (Dropout)          (None, 8, 8, 256)         0
_________________________________________________________________
flatten_2 (Flatten)          (None, 16384)             0
_________________________________________________________________
dense_3 (Dense)              (None, 260)               4260100
_________________________________________________________________
dense_4 (Dense)              (None, 130)               33930
_________________________________________________________________
batch_normalization_4 (Batch (None, 130)               520
_________________________________________________________________
dropout_9 (Dropout)          (None, 130)               0
_________________________________________________________________
dense_5 (Dense)              (None, 10)                1310
=================================================================
Total params: 5,385,332
Trainable params: 5,384,784
Non-trainable params: 548
_________________________________________________________________


Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 556s 9ms/step - loss: 0.4140 - acc: 0.8703 - val_loss:
1.3220 - val_acc: 0.6249
Epoch 2/15
60000/60000 [==============================] - 556s 9ms/step - loss: 0.0809 - acc: 0.9766 - val_loss:
0.1436 - val_acc: 0.9564
Epoch 3/15
60000/60000 [==============================] - 537s 9ms/step - loss: 0.0599 - acc: 0.9828 - val_loss:
0.0930 - val_acc: 0.9725
Epoch 4/15
60000/60000 [==============================] - 546s 9ms/step - loss: 0.0446 - acc: 0.9871 - val_loss:
0.0546 - val_acc: 0.9834
Epoch 5/15
60000/60000 [==============================] - 538s 9ms/step - loss: 0.0425 - acc: 0.9875 - val_loss:
0.0486 - val_acc: 0.9849
Epoch 6/15
60000/60000 [==============================] - 534s 9ms/step - loss: 0.0388 - acc: 0.9888 - val_loss:
0.0378 - val_acc: 0.9891
Epoch 7/15
60000/60000 [==============================] - 534s 9ms/step - loss: 0.0347 - acc: 0.9896 - val_loss:
0.0359 - val_acc: 0.9896
Epoch 8/15
60000/60000 [==============================] - 534s 9ms/step - loss: 0.0291 - acc: 0.9917 - val_loss:
0.0325 - val_acc: 0.9901
Epoch 9/15
60000/60000 [==============================] - 534s 9ms/step - loss: 0.0430 - acc: 0.9877 - val_loss:
0.0705 - val_acc: 0.9831
Epoch 10/15
60000/60000 [==============================] - 534s 9ms/step - loss: 0.0305 - acc: 0.9910 - val_loss:
```

```
0.0360 - val_acc: 0.9892
Epoch 11/15
60000/60000 [==============================] - 547s 9ms/step - loss: 0.0260 - acc: 0.9919 - val_loss:
0.0363 - val_acc: 0.9898
Epoch 12/15
60000/60000 [==============================] - 537s 9ms/step - loss: 0.0234 - acc: 0.9932 - val_loss:
0.0424 - val_acc: 0.9894
Epoch 13/15
60000/60000 [==============================] - 536s 9ms/step - loss: 0.0228 - acc: 0.9933 - val_loss:
0.0418 - val_acc: 0.9902
Epoch 14/15
60000/60000 [==============================] - 535s 9ms/step - loss: 0.0217 - acc: 0.9934 - val_loss:
0.0285 - val_acc: 0.9922
Epoch 15/15
60000/60000 [==============================] - 535s 9ms/step - loss: 0.0201 - acc: 0.9938 - val_loss:
0.0250 - val_acc: 0.9940
Wall time: 2h 14min 56s
```

In [11]:
```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy: {0:.2f}%'.format(score[1]*100))
```

```
Test score: 0.024988538761119707
Test accuracy: 99.40%
```

In [12]:
```
# Plot train and cross validation error
plot_train_cv_loss(trained_model, epochs)
```



On 4th epoch we find that validation error and train error comes together, so best value for epoch is between 2-4

Model 3 : with 7-Convolution Layer and 7X7 kernel

In [19]:
```
%%time
batch_size = 256

# Instantiate sequential model
model = Sequential()

# Add 1st hidden layer : Convolution Layer 1
conv_layer1 = Conv2D(8,
                         kernel_size=kernel_7X7,
                         activation="relu",
                         kernel_initializer='he_normal',
                         input_shape=input_shape)
model.add(conv_layer1)
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=max_pool_4X4,strides=(1,1),padding="same"))
model.add(Dropout(0.25))


# Add 2nd hidden layer : Convolution Layer 2
conv_layer2 = Conv2D(16,
                        kernel_size=kernel_7X7,
                        kernel_initializer='he_normal',
                        activation="relu")
model.add(conv_layer2)
model.add(MaxPooling2D(pool_size=max_pool_4X4,strides=(1,1),padding="same"))
model.add(Dropout(0.25))


# Add 3rd hidden layer : Convolution Layer 3
conv_layer3 = Conv2D(32,
                        kernel_size=kernel_7X7,
                        kernel_initializer='he_normal',
                        activation="relu")
model.add(conv_layer3)
model.add(MaxPooling2D(pool_size=max_pool_4X4,strides=(1,1),padding="same"))
model.add(Dropout(0.25))

# Add 4th hidden layer : Convolution Layer 4
conv_layer4 = Conv2D(64,
                        padding="same",
                        kernel_size=kernel_7X7,
                        kernel_initializer='he_normal',
                        activation="relu")
model.add(conv_layer4)
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=max_pool_4X4,strides=(1,1),padding="same"))
model.add(Dropout(0.25))


# Add 5th hidden layer : Convolution Layer 5
conv_layer5 = Conv2D(128,
                        padding="same",
                        kernel_size=kernel_7X7,
                        kernel_initializer='he_normal',
                        activation="relu")
model.add(conv_layer5)
model.add(MaxPooling2D(pool_size=max_pool_4X4,strides=(1,1),padding="same"))
model.add(Dropout(0.25))

# Add 6th hidden layer : Convolution Layer 6
conv_layer6 = Conv2D(256,
                        padding="same",
                        kernel_size=kernel_7X7,
                        kernel_initializer='he_normal',
                        activation="relu")
model.add(conv_layer6)
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=max_pool_4X4,strides=(1,1),padding="same"))
model.add(Dropout(0.50))

# Add 7th hidden layer : Convolution Layer 7
conv_layer7 = Conv2D(512,
                        kernel_size=kernel_7X7,
                        kernel_initializer='he_normal',
                        activation="relu")
model.add(conv_layer7)
model.add(MaxPooling2D(pool_size=max_pool_4X4,strides=(1,1),padding="same"))
model.add(Dropout(0.50))


# Convert data to 1-D array and perform normal MLP
model.add(Flatten())

# Convert to dense layer
model.add(Dense(520, activation='relu'))

# Convert to dense layer
```

```
model.add(Dense(250, activation='relu'))

# Convert to dense layer
model.add(Dense(125, activation='relu'))

# Add batch normalization
model.add(BatchNormalization())

# Add dropout
model.add(Dropout(0.50))

# Output layer
model.add(Dense(target_class_label_count, activation='softmax'))


# Summary of the model
print("Model Summary: \n")
model.summary()
print()
print()

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Run the model
trained_model = model.fit(x_train, y_train, batch_size = batch_size, epochs = epochs, verbose=1, valid
ation_data=(x_test, y_test))
```

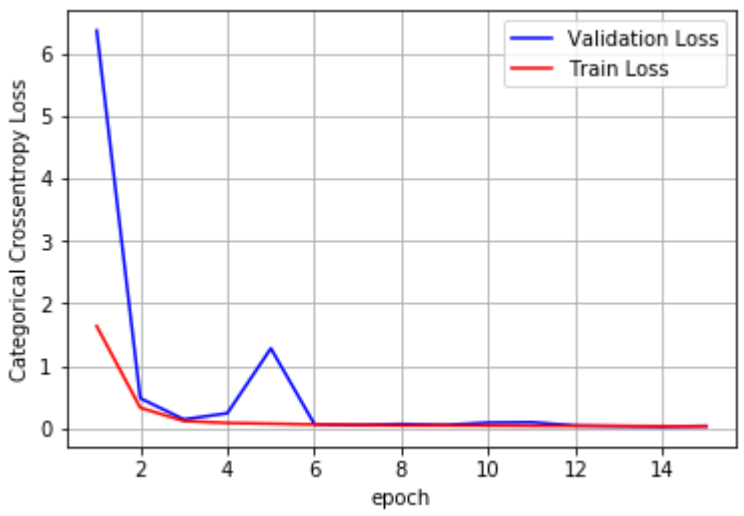
```
Model Summary:

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_27 (Conv2D)           (None, 22, 22, 8)         400
_________________________________________________________________
batch_normalization_12 (Batc (None, 22, 22, 8)         32
_________________________________________________________________
max_pooling2d_23 (MaxPooling (None, 22, 22, 8)         0
_________________________________________________________________
dropout_25 (Dropout)         (None, 22, 22, 8)         0
_________________________________________________________________
conv2d_28 (Conv2D)           (None, 16, 16, 16)        6288
_________________________________________________________________
max_pooling2d_24 (MaxPooling (None, 16, 16, 16)        0
_________________________________________________________________
dropout_26 (Dropout)         (None, 16, 16, 16)        0
_________________________________________________________________
conv2d_29 (Conv2D)           (None, 10, 10, 32)        25120
_________________________________________________________________
max_pooling2d_25 (MaxPooling (None, 10, 10, 32)        0
_________________________________________________________________
dropout_27 (Dropout)         (None, 10, 10, 32)        0
_________________________________________________________________
conv2d_30 (Conv2D)           (None, 10, 10, 64)        100416
_________________________________________________________________
batch_normalization_13 (Batc (None, 10, 10, 64)        256
_________________________________________________________________
max_pooling2d_26 (MaxPooling (None, 10, 10, 64)        0
_________________________________________________________________
dropout_28 (Dropout)         (None, 10, 10, 64)        0
_________________________________________________________________
conv2d_31 (Conv2D)           (None, 10, 10, 128)       401536
_________________________________________________________________
max_pooling2d_27 (MaxPooling (None, 10, 10, 128)       0
_________________________________________________________________
dropout_29 (Dropout)         (None, 10, 10, 128)       0
_________________________________________________________________
conv2d_32 (Conv2D)           (None, 10, 10, 256)       1605888
_________________________________________________________________
batch_normalization_14 (Batc (None, 10, 10, 256)       1024
_________________________________________________________________
max_pooling2d_28 (MaxPooling (None, 10, 10, 256)       0
_________________________________________________________________
dropout_30 (Dropout)         (None, 10, 10, 256)       0
_________________________________________________________________
conv2d_33 (Conv2D)           (None, 4, 4, 512)         6423040
_________________________________________________________________
max_pooling2d_29 (MaxPooling (None, 4, 4, 512)         0
_________________________________________________________________
dropout_31 (Dropout)         (None, 4, 4, 512)         0
_________________________________________________________________
flatten_3 (Flatten)          (None, 8192)              0
_________________________________________________________________
dense_6 (Dense)              (None, 520)               4260360
_________________________________________________________________
dense_7 (Dense)              (None, 250)               130250
_________________________________________________________________
dense_8 (Dense)              (None, 125)               31375
_________________________________________________________________
batch_normalization_15 (Batc (None, 125)               500
_________________________________________________________________
dropout_32 (Dropout)         (None, 125)               0
_________________________________________________________________
dense_9 (Dense)              (None, 10)                1260
=================================================================
Total params: 12,987,745
Trainable params: 12,986,839
Non-trainable params: 906
_________________________________________________________________


Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 1463s 24ms/step - loss: 1.6370 - acc: 0.3783 - val_los
s: 6.3652 - val_acc: 0.1684
Epoch 2/15
60000/60000 [==============================] - 2050s 34ms/step - loss: 0.3328 - acc: 0.9054 - val_los
s: 0.4841 - val_acc: 0.8590
Epoch 3/15
60000/60000 [==============================] - 1445s 24ms/step - loss: 0.1203 - acc: 0.9685 - val_los
s: 0.1466 - val_acc: 0.9627
Epoch 4/15
60000/60000 [==============================] - 1443s 24ms/step - loss: 0.0891 - acc: 0.9765 - val_los
s: 0.2444 - val_acc: 0.9392
Epoch 5/15
```

```
60000/60000 [==============================] - 1446s 24ms/step - loss: 0.0778 - acc: 0.9794 - val_los
s: 1.2826 - val_acc: 0.8897
Epoch 6/15
60000/60000 [==============================] - 1493s 25ms/step - loss: 0.0649 - acc: 0.9827 - val_los
s: 0.0703 - val_acc: 0.9810
Epoch 7/15
60000/60000 [==============================] - 1443s 24ms/step - loss: 0.0580 - acc: 0.9846 - val_los
s: 0.0572 - val_acc: 0.9836
Epoch 8/15
60000/60000 [==============================] - 1442s 24ms/step - loss: 0.0492 - acc: 0.9868 - val_los
s: 0.0713 - val_acc: 0.9796
Epoch 9/15
60000/60000 [==============================] - 1445s 24ms/step - loss: 0.0497 - acc: 0.9865 - val_los
s: 0.0572 - val_acc: 0.9843
Epoch 10/15
60000/60000 [==============================] - 1447s 24ms/step - loss: 0.0472 - acc: 0.9873 - val_los
s: 0.0941 - val_acc: 0.9733
Epoch 11/15
60000/60000 [==============================] - 1446s 24ms/step - loss: 0.0435 - acc: 0.9880 - val_los
s: 0.0997 - val_acc: 0.9711
Epoch 12/15
60000/60000 [==============================] - 1446s 24ms/step - loss: 0.0421 - acc: 0.9884 - val_los
s: 0.0468 - val_acc: 0.9868
Epoch 13/15
60000/60000 [==============================] - 1447s 24ms/step - loss: 0.0418 - acc: 0.9886 - val_los
s: 0.0373 - val_acc: 0.9910
Epoch 14/15
60000/60000 [==============================] - 1447s 24ms/step - loss: 0.0376 - acc: 0.9894 - val_los
s: 0.0303 - val_acc: 0.9910
Epoch 15/15
60000/60000 [==============================] - 1571s 26ms/step - loss: 0.0353 - acc: 0.9907 - val_los
s: 0.0411 - val_acc: 0.9891
Wall time: 6h 14min 36s
```

In [20]:
```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy: {0:.2f}%'.format(score[1]*100))
```

```
Test score: 0.041122954766452315
Test accuracy: 98.91%
```

In [21]:
```
# Plot train and cross validation error
plot_train_cv_loss(trained_model, epochs)
```



On 6th epoch we find that validation error and train error comes together, and then after follows the same path.

Observations :

---

1. Tried different CNN architectures on MNIST dataset.
2. 'Relu' is used as an activation function to develop deep CNN network.
3. 'Adam' is used as an optimizer to develop deep CNN network.
4. Introduced batch normalization, max-pooling and dropout in between hidden layers.
5. Got 99.35, 99.40 and 98.91 accuracies for 2,3 and 5 hidden layers.
6. Optimal epoch values are also calculated to avoid overfitting.